EEG Indices Distinguish Spatial and Verbal Working Memory Processing: Implications for Real-Time Monitoring in a Closed-Loop Tactical Tomahawk Weapons Simulation

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Abstract

This effort focused on developing EEG-derived indicators of verbal versus spatial working memory load. A wireless EEG headset acquired data during execution of both simple and complex tasks associated with a Tactical Tomahawk Weapons Control System (TTWCS). The results established the feasibility of characterizing EEG correlates specific to verbal and spatial working memory. The next goal is to leverage these real-time working memory indices as a feedback loop to direct closed-loop human-system interaction. Specifically, if the preliminary EEG indices derived in this study, in combination with other physiological or behavioral inputs, are shown to relate to the degree of working memory overload in the TTWCS or similar tasks, they could provide a valuable contribution to real-time adaptive aiding of human-system interaction.

1 Introduction

Working memory overload is one of the key contributors to operator errors during complex tasks. The capacity of human working memory has been defined as the number of items that can be held in conscious attention for use in a specific task or for later long-term storage (Baddeley & Logie, 1999). The constraints of working memory are particularly relevant during skill acquisition where working memory capacity is frequently exceeded. Traditional models (c.f. Baddeley & Hitch, 1974) characterize working memory as having two separate and relatively autonomous subsystems: verbal (i.e., phonological loop) and spatial (i.e., visuo-spatial sketchpad), but contemporary models suggest further disassociation (potentially based on sensory modality) (c.f. Miyake & Shah, 1999). Recent investigations suggest that working memory capacity can be enhanced by utilizing verbal, spatial, or alternative sensory modalities in a complementary manner (Wickens, 2002).

The development of an effective method for monitoring working memory load and delineating the verbal and spatial components could greatly enhance the speed and efficiency of human-system interaction. A real-time monitor could identify periods of spatial and/or verbal working memory overload and provide adaptive aiding, such as switching from verbal or spatial presentation formats, to meet operator requirements (Schmorrow, Stanney, Wilson, & Young, 2005). However, frequent switching between one modality or task and another may incur a "cost" due to stimulus competition, ambiguity, or distractions (Baddeley, 2003; Matlin, 1998). Thus, it is essential to develop an understanding of how best to leverage the multimodal capacity of working memory without incurring such costs.

As a first step towards developing a real-time neurophysiological working memory index that could trigger such adaptive aiding, a wireless electroencephalographic (EEG) system was used to acquire data during working memory tasks of varying complexity. In the first phase of the study, participants performed three simple working memory tasks: one spatial and two verbal, designed in accordance with methods previously reported (Proffitt, 2003). The simple verbal and spatial tasks used elements of a Tactical Tomahawk Weapons Control System (TTWCS) so that they could be integrated into a more operationally relevant simulated TTWCS environment that would serve as the testbed for the second portion of the study. The rationale for this design was that if a set of EEG parameters were identified that distinguished between the simple verbal and spatial tasks, these parameters could then be evaluated in

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the more complex TTWCS testbed. The initial goal of the first phase was to select a set of EEG variables optimized for discrimination of verbal from spatial processing in the simple tasks (Proffitt, 2003).

The second phase of the study was designed to evaluate the utility of the EEG variables in a complex TTWCS simulation task and to determine whether additional EEG parameters were required to provide accurate delineation of the spatial and verbal processing within the more complex task environment. The selected EEG variables would then serve as inputs to a neural net that used a combination of physiological parameters to identify relevant cognitive state changes while operators performed the TTWCS simulation tasks. The outputs of the neural net controlled the timing and introduction of multimodal augmentation strategies designed to optimize the distribution of perception and cortical processing within the TTWCS environment to take advantage of the totality of human capacity for multimodal communication. These studies represent the initial steps in building the foundation for designing a robust Command and Control (C^2) system that can adapt interaction techniques to meet specific user conditions.

2 Methods

The current study was performed in two phases. During the first phase, EEG data was acquired while participants performed simple working memory tasks. In the second phase, participants performed a complex working memory task, playing the role of a Tactical Strike Coordinator interacting with a simulated TTWCS environment.

2.1 Participants

For the Simple Working Memory Task experiment, 12 Lockheed Martin employees were studied. The participants were provided verbal instructions but no hands-on training prior to the start of each task. The tasks were presented in the following order: Missile ID, Mental Addition and Missile Location. Data from two participants were excluded from analyses. One participant was dropped due excessive EMG (muscle) artifact in the mono-polar channels due to the mastoid reference electrode. The second participant was dropped due to an inability to determine the start and end of each task due to missing time synchronization data.

Of the ten Lockheed Martin employees who participated in the Complex Working Memory Task study, data from seven participants were included for analyses. Two participants were dropped due to excessive EMG artifact in the monopolar channels due to the mastoid reference electrode. The third participant was dropped due to an inability to determine the start and end of each task due to missing synchronization data. Participants were provided a fixed timeframe for training on the TTWCS tasks in advance of their testing session.

2.2 Simple Working Memory Tasks

The three simple working memory tasks were designed to replicate experiments performed by Proffitt (2003). The tasks were designed to tap into both verbal and spatial working memory, such that they would provide differentiable EEG signatures.

2.2.1 Verbal Task – "Missile ID"

In this auditory recognition task, participants were presented with synthesized speech listing a set of two Missile Identifiers (ID) (e.g. 56U, 15P). After the set of Missile ID's were presented, the computer cued the user by saying the word "listen" and then "spoke" a series of Missile IDs. Participants responded via a keyboard as to whether or not a spoken Missile ID matched one of the sets previously presented.

2.2.2 Verbal Task – "Mental Addition"

In this computation task, participants were presented with a display containing a single number at the center of the display and instructed to respond to the number. A new number was presented each time the participant responded. Participants were instructed to add a series of numbers until prompted to report the total.

2.2.3 Spatial Task – "Missile Location"

In this "grid-task", participants were presented with a 5 x 5 grid that contained from three to five missiles. The display was shown for a brief interval and then removed. After approximately 40 seconds, the grid reappeared with a subset of the missiles shown. Participants were instructed to indicate the locations of missing missiles. Participants had approximately 4 seconds to indicate locations of missing missiles before the grid disappeared.

2.3 Complex Working Memory Tasks

In the Complex tasks the operator performed the role of a Tactical Strike Coordinator interacting with a simulated TTWCS environment. It is the job of the Tactical Strike Coordinator to assign missile strikes to specific targets, and to monitor and reassign missiles to "emergent targets" as these events occur. The scenarios used to select EEG correlates included performing assessment of missile coverage zones, referred to as the "Location Task", and retargeting missiles based on emerging targets of higher priority, referred to as the "Retarget Task".

2.3.1 Spatial Task – "Location"

The location task (Figure 1) was separated into three parts: encoding, rehearsal, and recall. During the "encoding" period, participants were given 15-seconds to study the location and 10-minute coverage zone (i.e., circular region around each missile shown in Figure 1 below) of each missile and the associated targets. During the 45-second "rehearsal" period, the coverage zone circles were removed, however participants were provided the opportunity to continue memorizing the initial information that was previously displayed. During the "recall" period, participants were provided 30-seconds to identify targets that were/were not covered by any missile's coverage zones. Since most participants completed their "recall" responses well within the allotted time, only the first 12 seconds of the recall period were analyzed.

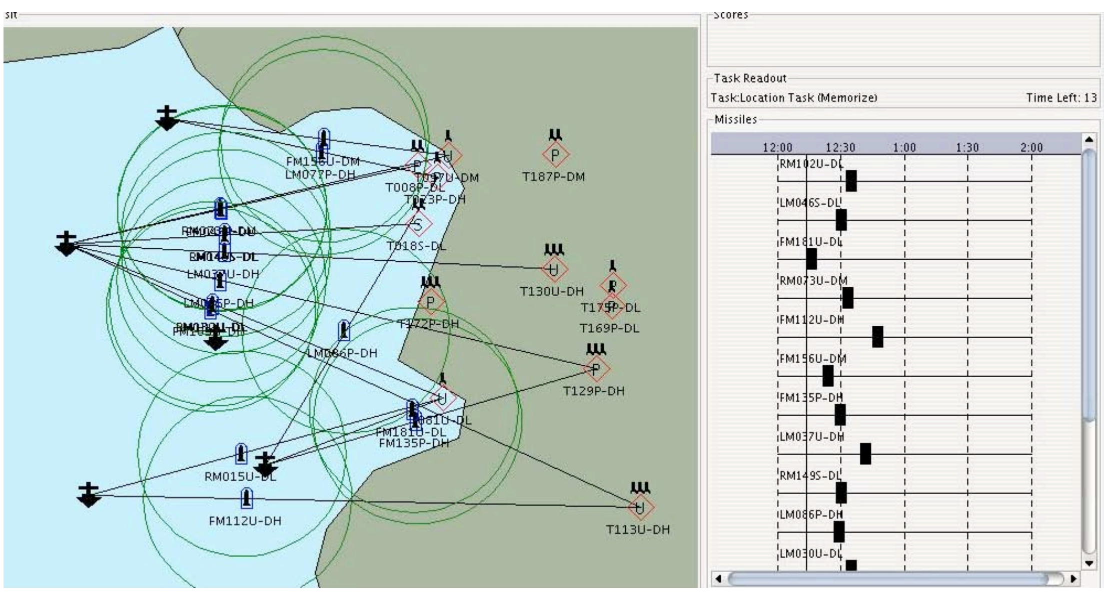

Figure 1: Screen presentation during location task

2.3.2 Verbal Task – "Retarget"

The "Retarget" task (Figure 2) required participants to retarget missiles based on higher priority emergent targets. Participants were provided 10 minutes to reallocate missile coverage to as many emergent targets as possible, while maintaining coverage on as many high and medium default targets as possible. There were four rules for retargeting missiles: a) missile warhead types must match target warhead types, b) the number of missiles servicing a target must match the number of missiles required by that target, c) highest priority emergent targets should be retargeted first, d) only Loiter or Retarget (L/R) missiles may be retargeted. The information available for retargeting was presented in the text below each missile and target. Emergent targets were colored red and their appearance and locations were randomly assigned throughout the task. The Task Readout, to the right of the missile-target map,

provided information to the participant helpful in determining a retargeting strategy. This information included the amount of time from missile-target intercept and closest missile to emergent target.

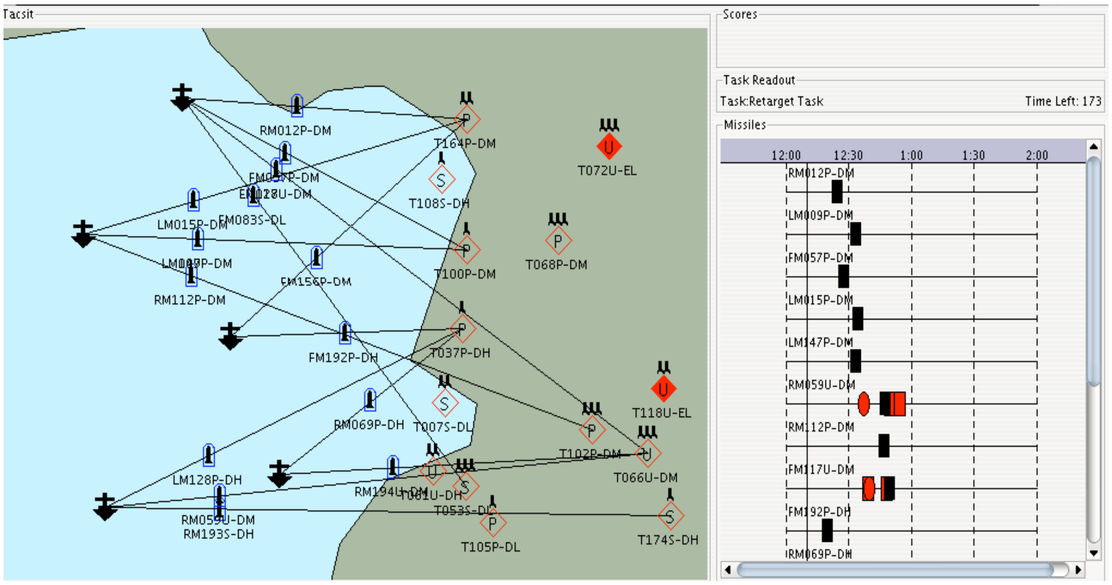

Figure 2: Screen presentation during retarget task

2.4 Data Acquisition

2.4.1 Tactical Tomahawk Weapons Simulation (TTWCS) Test bed

The TTWCS simulation test bed ran on an Intel Pentium 4- 3.0 GHz (800MHz FSB - 1MB Cache) computer with 1 GB (2 64-bit wide DDR data channel) memory, a 60G 7200rpm high performance drive, and an ATI Radeon Mobility Integrated 256MB DDR Video, with Accelerated OpenGL and 8x ultraAGP. The operating system was Red Hat/Fedora Linux with customized 2.6.9 kernel (Fedora Core 2 with latest updates). The visual interface was presented on a 17” WSXGA+ (1680x1050) screen. All user responses were with standard keyboard and 2-button mouse. The audio was presented via 6 channel desktop speakers based on AC’97 2.2 virtual 6-channel output onboard sound.

2.4.2 EEG Acquisition

A modified wireless EEG headset acquired data from 9 monopolar sites referenced to linked mastoids (F3, F4, Fz, C3, C4, Cz, P3, P4, POz) and 2 bipolar sites (Cz-POz, Fz-POz) (see Berka 2004 for basic EEG headset details). The EEG transceiver unit was interfaced to a laptop computer (Pentium 2.4 MHz with 512 RAM and a Windows XP operating system) that operated the EEG acquisition software used to generate an EEG record and provide time synchronization data to the TTWCS test bed via a TCP-IP network protocol.

2.5 Data Reduction

For the Simple Working Memory Tasks, approximately 30 one-second epochs of EEG data per task were extracted from the three task conditions (i.e., Missile ID, Mental Addition, and Missile Location). For the Complex Working Memory Tasks, seventy one-second epochs were extracted for the training data set from each of two segments: the encoding segment of the “location” task and the retargeting segment of the “retarget” task. The balance of data from the tasks was used for testing discriminant function models (see section 2.5).

Processing of the EEG included identification and decontamination or rejection of artifacts, including eye blinks, spikes, saturation, excursions, and EMG, using previously published procedures (Berka 2004). The EEG power

spectra for each 1 Hz bin between 3 – 40 Hz were computed for each channel, generating a total of 418 EEG variables from 11 channels for each one-second epoch.

One of the long-term goals of the project is to optimize the selection of sensor locations, number of channels and number of EEG variables to provide accurate classifications while minimizing the amount of data acquired. In order to assess a variety of headset configurations, a total of eight EEG data sets were created. The "Mid-line Bipolar" data set included only the 1 Hz bins from FzPOz and CzPOz for the Simple and Complex Working Memory Tasks, respectively. The "Mid-line All" data sets included the bi-polar sites plus the mono-polar sites Fz, Cz and POz. The "Lateral" data sets included the 1 Hz bins from the mono-polar sites F3, F4, C3, C4, P3 and P4. The "Mid - Lat" data sets included all bi-polar and mono-polar data from all 11 channels.

2.6 Variable Selection and Model Development

Three- and two-class discriminant function models were used to classify data from the Simple and Complex Working Memory Tasks, respectively. Step-wise analysis was used to select predictive variables for each of the eight data sets. The discriminant function models generated with variables and coefficients derived from the Simple (Complex) Working Memory Task for each data set were applied to the Complex (Simple) Task data to evaluate the influence of variable selection. Individualized discriminant function models were derived to assess the benefit of fitting coefficients to the unique EEG patterns of each participant.

3 Results

3.1 Classification Models During the Simple Working Memory Task

The results from four discrimant function models applied to the Simple Working Memory Tasks are presented in Table 1. The Mid-line Bipolar model provided surprisingly good classification for the Missile ID and Missile Location tasks (using just two channels of data and eleven variables), but, due to poor classification during the Mental Addition task, reported an overall classification accuracy of only 50%.

The Lateral Model provided better classification in the Missile ID task compared to the Mid-line All with a similar number of channels and variables, however the overall classification accuracies were similar. The Lateral Model required an additional three sensor sites to achieve the better performance in the Missile ID task. The Mid-Lat Model was clearly superior, although nine sensors, 11 channels and 43 variables were required to achieve these results. Table 2 presents the number of variables selected from each of the sensor sites for the Mid - Lat Model. The rank order of the top seven variables (partial R^2 values > 0.03) was C4 37Hz, P4 11Hz, P3 13Hz, CzPOz 31Hz, Cz 32Hz, CzPOz 18Hz, and C4 26Hz.

Table 1: Classification Accuracy of Three-Condition Simple Task Model

Model	# Sensors	# Channels	# Variables	Percent of epochs correctly classified			Class Accuracy
				Verbal - Missile ID	Verbal- Mental Addition	Spatial - Missile Location	
Mid-line Bipolar	3	2	11	60.4	40.6	61.5	50.8
Mid-line All	3	5	22	65.7	60.7	67.4	64.5
Lateral	6	6	26	75.2	60.3	65.1	66.9
Mid – Lat	9	11	43	77.8	76.4	76.6	77.0

Table 2: Mid – Lat Simple Model: Number of Variables Selected by Sensor Site

Site	**Monopolar**			**Bipolar**
	Left	Right	Midline	

Frontal	1	5	0	FzPOz	5
Central	6	5	3	CzPOz	6
Parietal	2	6	3*	B-Alert Class	1
Totals	9	16	6	12	

* The midline sensor is parietal occipital (POz)

3.2 Classification Models During the Complex Working Memory Task

The classification distribution trends across the four models for the Complex Tasks were similar to the Simple Task with the Mid-Lat sites providing optimal classification accuracy. For this reason, only results from the Mid-Lat Model are reported. Interestingly, the number of variables selected to discriminate the Complex Tasks was significantly reduced compared to the Simple task from 43 to 11 (Table 3 and 5). The rank order of variables with a partial R^2 values > 0.03 were P4 27Hz, P4 36Hz, and Fz 12Hz. Consistent with the Simple Task, the largest number of variables was selected from the lateral right region (Table 3). Table 4 presents the classification accuracy of the Two-Class Mid-Lat model with variables selected from the Complex Task (second row of data) applied to the three segments of the Location task and two segments of the Retarget task.

Table 3: Mid – Lat Complex Model: Number of Variables Selected by Sensor Site

Site	Monopolar			Bipolar	
	Left	Right	Midline		
Frontal	1	1	0	FzPOz	0
Central	1	2	2	CzPOz	1
Parietal	0	2	1*	B-Alert Class	0
Totals	2	5	3	1	

* The midline sensor is parietal occipital (POz)

3.3 Influence of Variable Selection on Classification Models

Due to the substantial difference in the number of variables selected for the Simple vs. Complex Tasks, a Three-Class Simple Task Model using the Complex Task variables and a Two-Class Complex Task Model using the Simple Task variables was developed. The result in Table 4 show that the classification accuracies of the two models applied to the Complex Task data were relatively similar. However, the results in Table 5 show that the Complex task variables are unable to discriminate the Simple Tasks better than chance.

Table 4: Results for Complex Task Models Using Variables from Simple vs. Complex Tasks

Model	Variable Type	Percent of epochs classified Verbal (V) or Spatial (S)									
		Spatial Task - Location						Verbal Task - Retarget			
		Encoding		Rehearsal		Recall		Encoding		Retarget	
		S	V	S	V	S	V	S	V	S	V
Mid – Lat	Simple	65.8	34.2	62.6	37.4	51.6	48.4	48.0	52.0	37.6	62.4
	Complex	67.1	32.9	58.9	41.1	50.0	50.0	43.0	57.0	33.9	66.1

Table 5: Results for Simple Task Models Using Variables from Simple vs. Complex Tasks

Model	Variable Model	# Variables	Percent of epochs correctly classified			Class Accuracy
			Verbal - Missile ID	Verbal- Mental Addition	Spatial - Missile Location	
Mid and Lat- All	Simple	43	77.8	76.4	76.6	77.0
Mid and Lat- All	Complex	11	53.5	55.0	39.5	49.5

To determine if the large difference in the number of simple versus complex variables required to discriminate between the tasks was caused by the additional task in the Simple Model, an alternative Two-class model was evaluated to compare only the verbal ("Missile ID") and spatial ("Missile Location") sub-tests of the Simple Tasks. This model required 34 EEG variables to accurate classify the two states, still significantly more variables than the 11 required for the Complex Task.

3.4 Fitting Model Coefficients to Accommodate Individual Differences in EEG

Table 6 presents the classification accuracies for individual participants using the Two-Class Model with the Simple Task variables and group discriminant function coefficients. These results demonstrate wide variability in the classification accuracies. Table 7 presents findings from Two-Class models using the same variables, with discriminant function coefficients fitted to the individual's EEG patterns.

Table 6: Classification Accuracy Two-Class Model Using Group Coefficients

Participant Number	Percent of epochs classified Verbal (V) or Spatial (S)									
	Spatial Tasks						Verbal Task			
	Encoding		Rehearsal		Recall		Encoding		Retarget	
	S-E	V-R	S-E	V-R	S-E	V-R	S-E	V-R	S-E	V-R
551	48.7	51.3	34.7	65.3	22.5	77.5	65.9	34.1	54.2	45.8
552	91.2	8.8	77.0	23.0	71.8	28.2	77.8	22.2	70.8	29.2
553	38.9	61.1	55.6	44.4	29.6	70.4	13.3	86.7	16.0	84.0
554	63.7	36.3	65.3	34.7	58.3	41.7	46.2	53.8	40.8	49.2
555	73.6	26.4	73.4	26.6	57.5	42.5	41.7	58.3	24.5	75.5
556	70.9	29.1	57.4	42.6	64.1	35.9	30.8	69.2	11.8	88.2
557	74.6	25.4	74.1	25.9	51.4	48.6	53.1	46.9	37.1	62.9
Mean	65.9	34.1	62.5	37.5	50.7	49.3	47.0	53.0	36.4	63.6

Table 7: Classification Accuracy Two-Class Mid-Lat Model Using Individualized Coefficients

Participant Number	Percent of epochs classified Verbal (V) or Spatial (S)									
	Spatial Task - Location						Verbal Task - Retarget			
	Encoding		Rehearsal		Recall		Encoding		Retarget	
	S-E	V-R	S-E	V-R	S-E	V-R	S-E	V-R	S-E	V-R
551	94.1	5.9	89.3	10.7	92.5	7.5	27.3	72.7	17.7	82.3
552	77.5	22.5	52.3	46.7	43.6	56.4	30.6	69.4	32.9	67.1
553	93.7	6.3	88.9	11.1	88.9	11.1	63.3	36.7	21.7	78.3
554	79.0	21.0	58.9	41.1	47.2	52.8	20.5	79.5	21.9	78.1
555	89.3	10.7	79.7	20.3	70.0	30.0	47.2	52.8	12.4	87.6
556	95.3	4.7	77.0	23.0	76.9	23.1	46.1	53.9	11.3	88.7
557	88.7	11.3	87.0	13.0	32.4	67.6	25.0	75.0	15.1	84.9
Mean	88.2	11.8	76.2	23.7	64.5	35.5	37.1	62.9	19.0	81.0

4 Conclusions

This paper presents one model approach to selecting EEG parameters that can be implemented in systems designed to monitor and interpret real-time cognitive state changes. Previous work by the investigative team (Berka, 2004, Berka, 2005) validated this approach to development of an EEG-based closed loop system where EEG correlates of mental workload were first established and validated in a series of simple tasks. The EEG-workload measures were subsequently validated in a complex Aegis simulation environment and were used successfully to control the pacing of stimulus presentation to optimize performance.

These data establish the feasibility of characterizing EEG correlates specific to verbal and spatial working memory in both simple and complex task environments. The variables derived from this analysis can be computed in real-time to provide a second-by-second assessment of verbal and spatial processing. The investigators acknowledge that the terms "verbal" and "spatial" apply only within the context of the tasks and conditions designed for the TTWCS simulation testbed. Although the experimental design team attempted to create task conditions that required predominantly verbal or spatial processing to provide data for selection of EEG parameters, the purity of these conditions, particularly in the complex tasks is questionable.

The difference in the number of EEG variables selected to discriminate Simple Task in comparison to the number required for the Complex Task (i.e., 43 vs. 11) suggests that the two complex tasks were more distinctive as reflected in their EEG characteristics than the three simple tasks, so fewer variables were required. An alternative 2-class model was evaluated to compare only the verbal (“Missile ID”) and spatial (“Missile Location”) sub-tests of the Simple Tasks. This model required 34 EEG variables to accurate classify the two states, still significantly more variables than the 11 required for the Complex Task. It is also possible that the Simple Task may have required more variables for accurate classification due to the limited attention required to perform the sub-tasks, resulting in greater variability in EEG activity within and between individuals.

Data from the complex tasks reveal that the patterns of EEG associated with “location” were distinctive from those observed during “retargeting”. It is possible that the complex tasks were more engaging than the simple tasks and elicited overall a greater percentage of focused time-on-task. Interestingly, the EEG variables selected for the Simple Task model provided similar classification accuracy when applied to the Complex Task, but those selected for the Complex Task were not effective in discriminating the simple sub-tasks. This finding suggests that the applicability of variables selected for one task may or may not be universally applied to other tasks and should be investigated as a component of model development.

The decision on how to accommodate individual differences is relevant to all aspects of model building in the design of closed-loop systems. Although the fitting of the discriminant function coefficients to each individual demonstrated a marked improvement on the consistency of correct classifications across participants the “classification accuracies” of the various models should be interpreted with some caution. Distinctive patterns of EEG classifications may actually reflect differences in strategic approach to the task demands or differential allocation of verbal and spatial memory. More detailed investigations of the relationship of task performance and EEG classifications on a second-by-second basis are required to better understand these associations. In addition, post-test interviews should be conducted to determine whether participants were employing unique strategies for completing the tasks.

If these preliminary data are replicated and the EEG indices, in combination with other physiological or behavioral inputs, are shown to relate to the degree of working memory overload in the TTWCS or similar tasks, they could provide a valuable contribution to real-time adaptive aiding of human-system interaction. The goal of the present model approach was to provide inputs to a neural-net based system that would employ augmentation strategies designed to take advantage of the totality of human capacity for multimodal communication. More specifically, the system involves adaptive multimodal mediation and attention alerting mechanisms, which incorporate multiple display strategies to invoke alternate sensory modalities given a TTWCS user’s current cognitive state as measured by real-time biophysical data. Based on output from the physiological sensors, as well as an understanding of current system state (i.e., which verbal and spatial tasks are currently being performed and their relative loading), alternate modality display strategies can be employed (i.e., modality-based task switching/augmenting). Any such aiding must be implemented judiciously, as any gains realized could be tempered if the costs for modality switching are high.

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